REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704-0188

1. REPORT DATE *(DD-MM-YYYY)*	2. REPORT TYPE	3. DATES COVERED *(From - To)*
01-06-2001	Technical	10-04-2000 to 09-04-2001

4. TITLE AND SUBTITLE

Reconfigurable Network of Networks for
Multi-Scale Computing

5a. CONTRACT NUMBER

5b. GRANT NUMBER

ONR N00014-99-1-0884

5c. PROGRAM ELEMENT NUMBER

6. AUTHOR(S)

Jeffrey P. Sutton, M.D., Ph.D.

5d. PROJECT NUMBER

5e. TASK NUMBER

5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)

General Hospital Corporation
Fruit Street
Boston, MA 02114

8. PERFORMING ORGANIZATION REPORT NUMBER

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)

Office of Naval Research - Prog Officer: Dr. Joel L. Davis ONR 342CN
Ballston Centre Tower One
800 North Quincy Street
Arlington, VA 22217-5660

10. SPONSOR/MONITOR'S ACRONYM(S)

ONR

11. SPONSORING/MONITORING AGENCY REPORT NUMBER

12. DISTRIBUTION AVAILABILITY STATEMENT

Approved for Public Release

13. SUPPLEMENTARY NOTES

14. ABSTRACT

The Network of Networks (NoN) model, which is a neurobiologically motivated smart algorithm co-developed by the PI, is being applied for rapid and accurate image processing of forward and side scan sonar images in turbid environments. The model is also being used as a platform for rapid distributed communications for autonomous vehicles. Both of these applications build upon unique features of the NoN for reconfigurable computing across multiple scales of organization, and the approach has direct relevance to several enabling technologies for Future Naval Capabilities.

15. SUBJECT TERMS

neural networks, sonar, autonomous vehicles, image enhancement, communications

16. SECURITY CLASSIFICATION OF: a. REPORT	b. ABSTRACT	c. THIS PAGE	17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
UU			SAR		Jeffrey P. Sutton
					19b. TELEPONE NUMBER *(Include area code)* (617) 726-4350

OFFICE OF NAVAL RESEARCH

6.1 Program Review - Sensory and Motor Adaptive Control

April 23, 2001

Potomac Institute for Policy Studies
Arlington, VA

Sponsor: Joel Davis, Ph.D. ONR 342CN

RECONFIGURABLE NETWORK OF NETWORKS FOR MULTISCALE COMPUTING

Jeffrey P. Sutton, M.D., Ph.D.

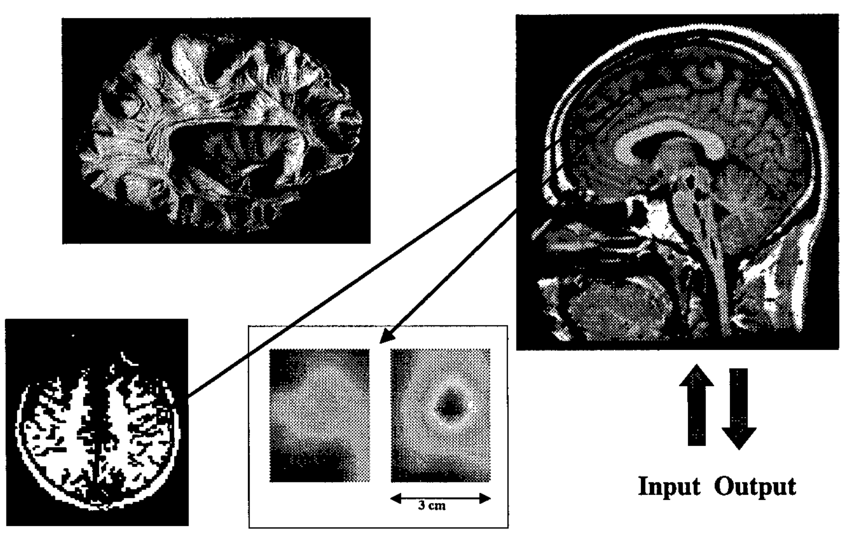
MGH Neural Systems Group
Harvard – MIT Division of Health Sciences and Technology
Boston, MA

Contact: sutton@nmr.mgh.harvard.edu

Project Objectives

- **Identify neural system features relevant to**
  - image enhancement & object identification in turbid conditions
  - communications for reconfigurable networks across scales
- **Implement these features for**
  - sonar image processing
  - systems of model autonomous vehicles (AVs)
- **Develop and deliver**
  - algorithms for mine detection, classification and identification (algorithm fusion)
  - demonstrations of simulated AV network dynamics based on neural system rules and properties

Neural System Technologies



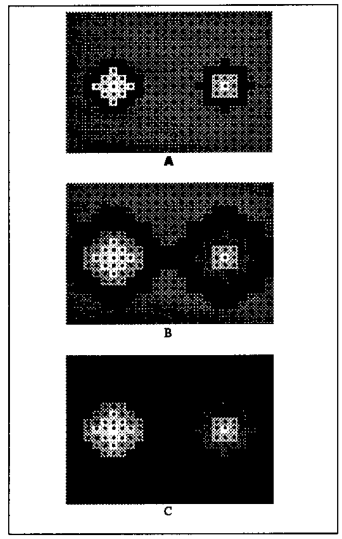
fMRI DOT Massachusetts General Hospital

Network of Networks (NoN) Simulations

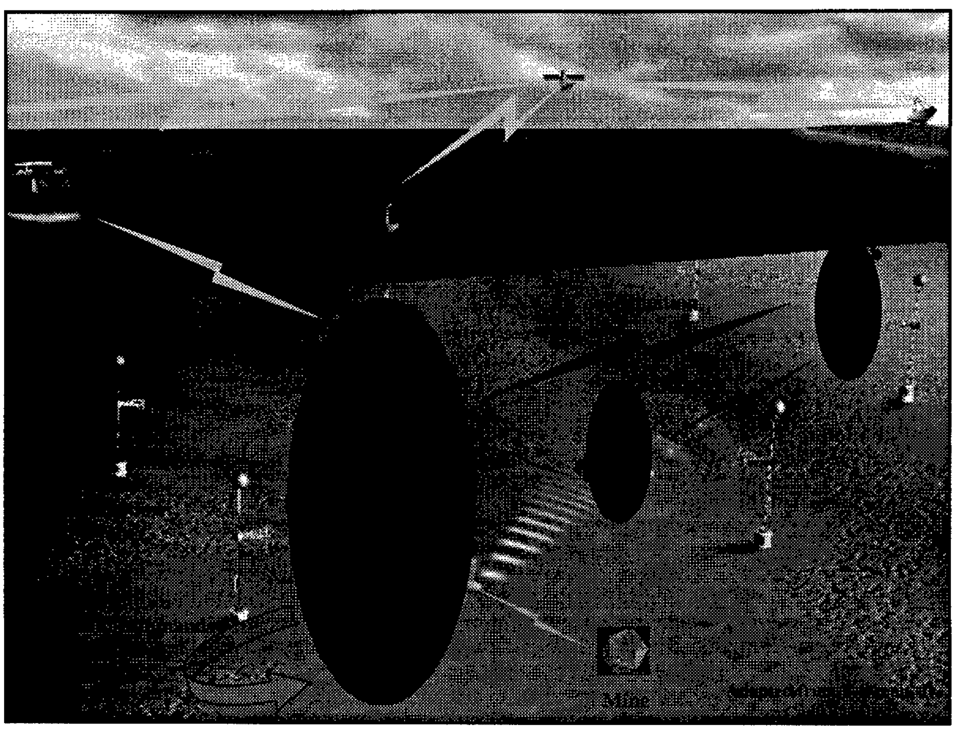
432 Networks

- Platform for computing at multiple scales simultaneously
- High capacity connectivity
- Dynamically reconfigurable networks
- Distributed, collaborative planning and data integration
- Adaptable to changing environment – sensory processing, decision making, action and control
- Autonomous operations

12 FNCs and Required Enabling Capabilities



Sutton JP, Anderson JA. System and method for high speed computing and feature recognition capturing aspects of neocortical computation. U.S. patent 5,842,190. 1998 Nov 24.



Naval Mine Threat and FNC for MCM

- Threats depend upon environment
- AVs have sensors, communication, energy, intelligence and mobility
- Enabling capabilities include rapid and automated mine detection, classification and identification
- Use of sensor <u>and</u> algorithm fusion

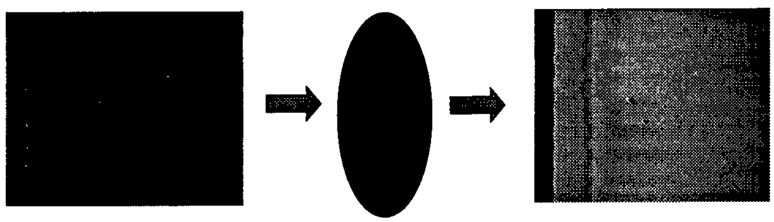
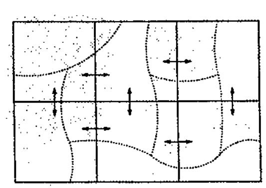
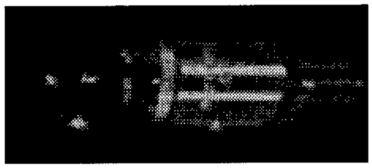


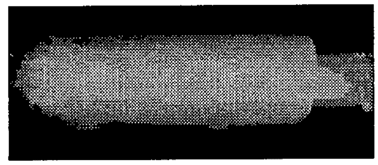
Image Reconstruction Under Turbid Environments

- Given ultrasound data of model mine blurred non-uniformly (undistorted images and dimensions of object not known)
- Data consisted of 200 contiguous slices, 550 x 200 pixels each
- Intermediate levels of clustering identified by a variance measure (λ values)
- Gradient decent using weights which depended upon the context (underwater environment) and λ values
- 3-D reconstruction by course graining over 16 slices

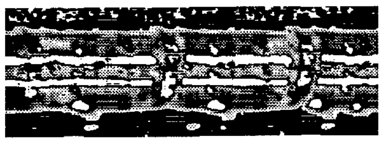




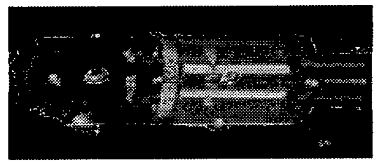
Initial (blurred) image



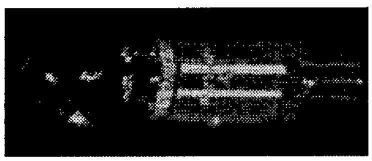
3D overlay with compression



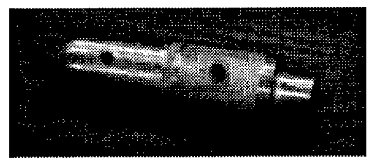
λ map revealing space variant distortion with uniform profile



Feature extraction



Enhanced image



Guan, Anderson, Sutton. *IEEE Trans NN*, 1997

Sutton JP, Guan L, inventors. System and method for image regularization in inhomogeneous environments using clustering in neural networks. U.S. patent 5,978,505. 1999 Nov 2.

Naval Sensor Data Database

Side Scan Sonar 0 Images

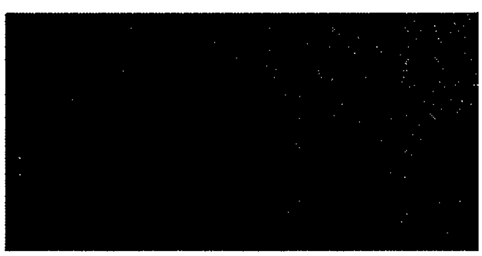


Image S1000206

Pseudocolor λ Map
5×5 window
λ ranges: below 40, 40-70, 70-100 and above 100

Sutton, Sha, Perry, Guan. ***Proc Inter Soc Optical Eng*, 1999**

Naval Sensor Data Database

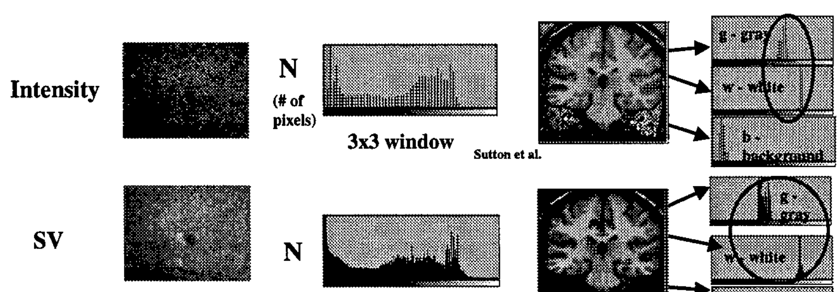
Side Scan Sonar 3 Images

- 22 400x400 pixel images analyzed containing 62 targets
- Scaled variance (SV) transformation without enhancement
- Data compression using binning of SV ranges (λ map)
- Mine detection based on regions of 8-20 pixels of uniform λ

- Image
- Scaled Variance (SV) Representation
  - enhanced contrast by transforming, using 3x3 window:

scaled mean intensity $\overline{I}_s(i,j)=\sum_{a=-1}^{1}\sum_{b=-1}^{1} I(i+a,j+b)/\beta=\frac{9}{\beta}\overline{I}(i,j)$

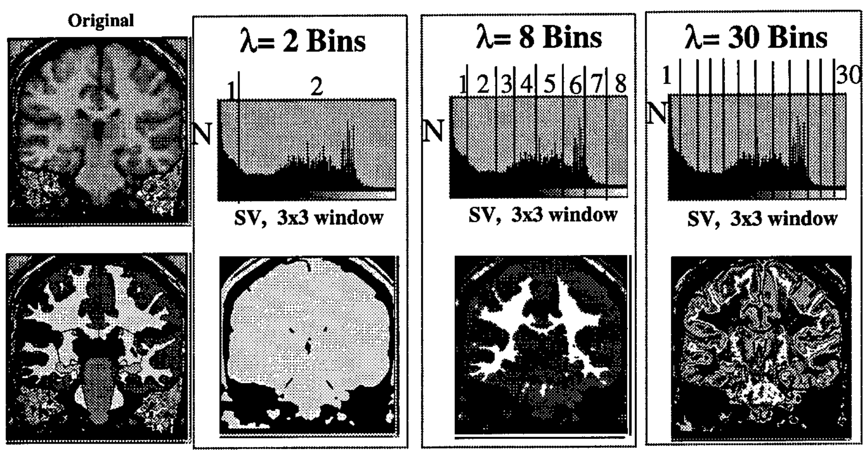
SV $$V_s(i,j)=\sum_{a=-1}^{1}\sum_{b=-1}^{1}\left[I(i+a,j+b)-\overline{I}_s(i,j)\right]^2/\beta$$
$$=\frac{9}{\beta}V(i,j)+\frac{(\beta-9)^2}{\beta^3}[I(i,j)]^2+6\frac{\beta-9}{\beta^2}I(i,j)\times\sqrt{V(i,j)}$$



Section of SI020000

Sha, Kennedy, Sutton *AI Med*, In press

- **Bin SV ranges (Consolidation), equi- / non-equipartitioning λ maps**

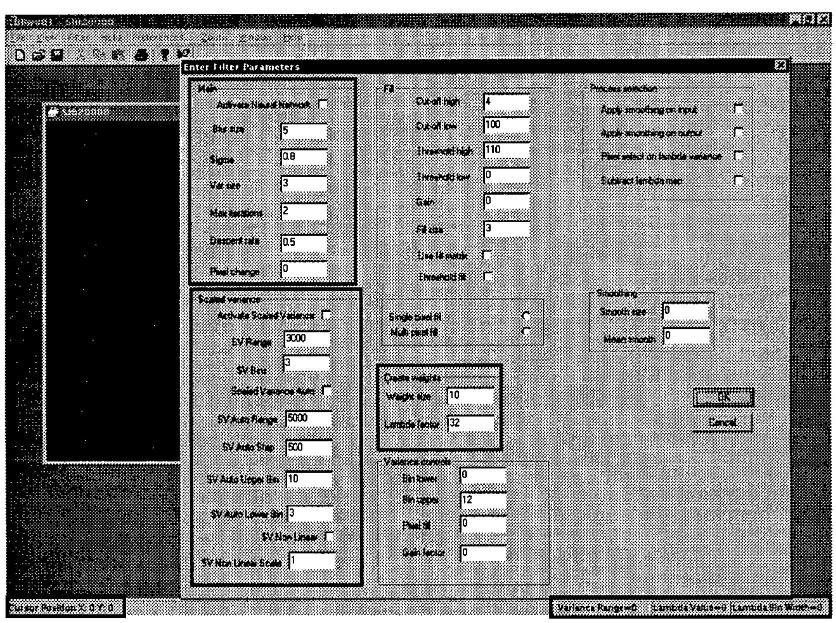


Manual Segmentation
MGH CMA

Sha and Sutton, *Info Sci*, In press
Invention Disclosure filed – Automated segmentation / classification

- **Detection → Classification / Identification**

eNCog Algorithms + GUI

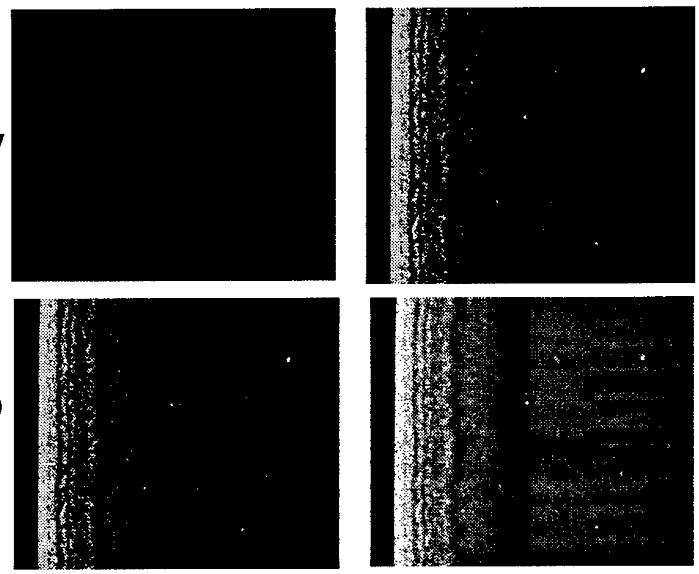


Naval Sensor Data Database

Side Scan Sonar 3 Image SI020007

SI020007

R 10,000
E B 4



R 10,000
E B 10

R 10,000
nonE B 12

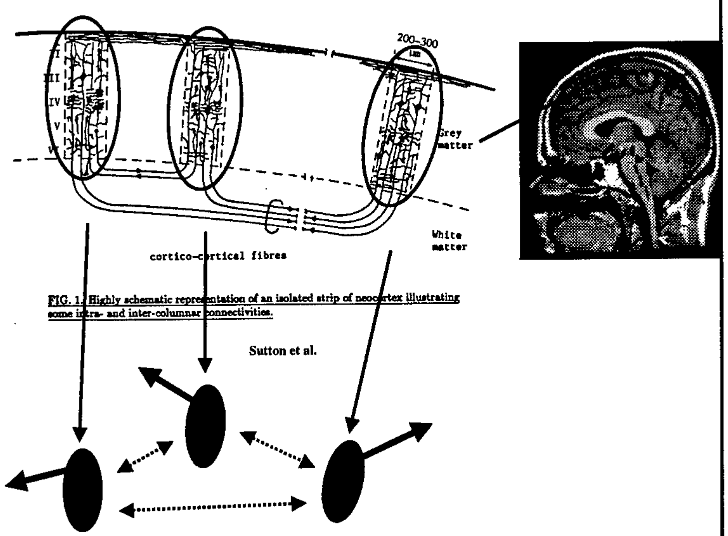
Naval Sensor Data Database

Side Scan Sonar 3 Images

Results

- **Without training on sample side scan targets (identification), classification of mine-like objects using 3x3 window, β=16 in SV equation, full SV range, 12 non-equipartitioned bins:**
  - **TP=59, FP=24, FN=3 over 22 images**
  - **Sensitivity = TP / (TP + FN) = 95%**
  - **PPV = TP / (TP + FP) = 71%**
  - **Typical FP rate is 0.5 – 1.0 suspect target per image**
- **Complementary to other mine hunting algorithms – useful for algorithm fusion CSS Dahlgren Division (NSWC visit 1 Mar 2001)**

Network of Networks Architecture



AVSYS Architecture

Collection of N AVs, $X_1, X_2, \ldots, X_N$, where each AV functions as an attractor neural network

S(t) encodes data characterizing source emitters, targets, other AVs, ...

The degree of match or overlap between **S**(t) and a template can be expressed by an overlap function $M_{ij}(t)$, where i indexes the template and j indexes the neural network (AV)

For a *network* of AVs, construct an overlap matrix, where each column is associated with a single AV

$$\mathbf{M(t)} = \begin{pmatrix} M_{11}(t) & \cdots & \cdots & M_{1N}(t) \\ \vdots & & & \vdots \\ \vdots & & & \vdots \\ M_{i1}(t) & \cdots & \cdots & M_{iN}(t) \end{pmatrix}.$$

M(t) is a function of time due to changes in
- the signal **S**(t)
- the position $\mathbf{r}_j(t)$ of X_j, which influences the X_j's classification of components of **S**(t)
- the templates, due to learning or external inputs (e.g., from a command center)

Mode 0 Dynamics

Baseline scenario of winner take all dynamics

AVs act independently and adjust their position to increase their overlap with the source component that most overlaps with a template

Communication among the AVs only occurs when an AV reaches $\max\{M_{ij}(t)\} \geq \theta$

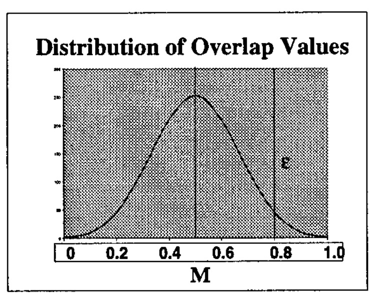
Mode 1 Dynamics

Implements weakly interacting dynamics among the AVs

Each X_j determines its overlaps $M_{ij}(t)$ and transmits those values exceeding a noise threshold, ε, to all the other AVs

Classification occurs when $M_{ij}(t) \geq \theta$ or

$$\sqrt{\sum_{j=1}^{N} \left(M_{ij}(t) \geq \varepsilon\right)^2 / n} \geq \theta .$$



$\max\{M_{ij}(t)\}$ values are determined across AVs (index j) rather than across templates (index i)

Allows for conflict resolution

Transient specialization of AV roles

Mode 2 Dynamics

Implements weakly interacting dynamics among the AVs

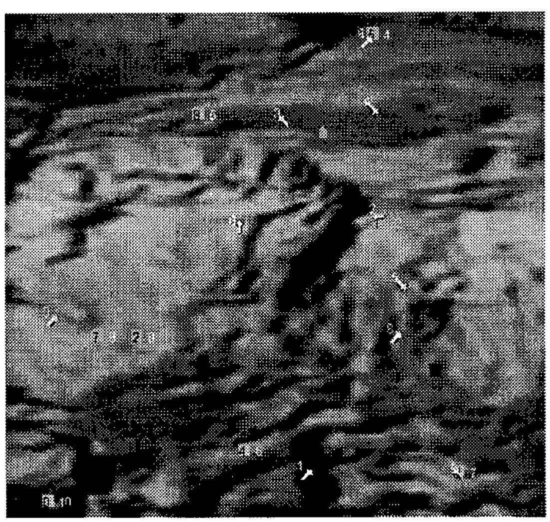
Similar to Mode 1 except that classification occurs when $M_{ij}(t) \geq \theta$ or

$$\sum_{k} \sum_{j=1}^{N} C_k \left(M_{ij}(t) \geq \varepsilon\right)^{\gamma_k} \geq \theta \quad .$$

More aggressive than Mode 1 – added value of all AVs with $M_{ij}(t) \geq \varepsilon$

Transient specialization of AV roles

AVSYS_UUV Algorithm and GUI



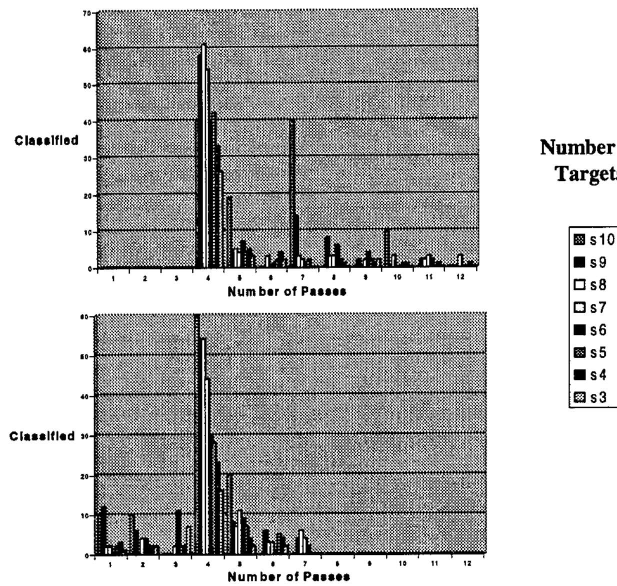
RESULTS Classification Performance of 10 UUVs Mine Targets

Mode 0

$\varepsilon=1, \theta=0.9$

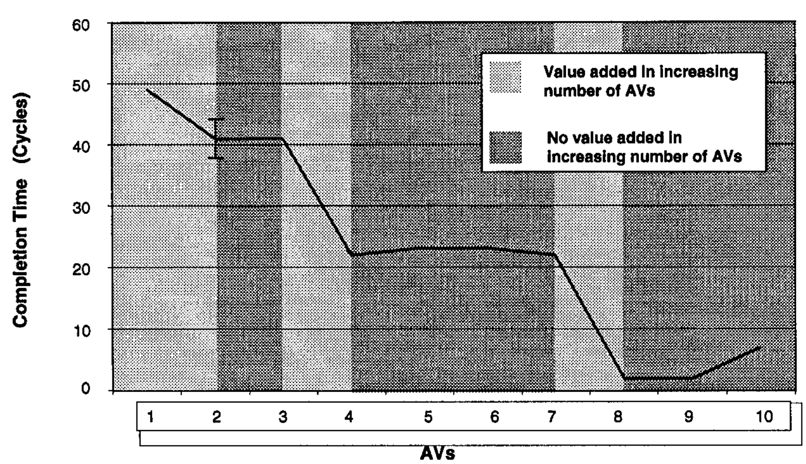
Mode 1

$\varepsilon=0, \theta=0.9$

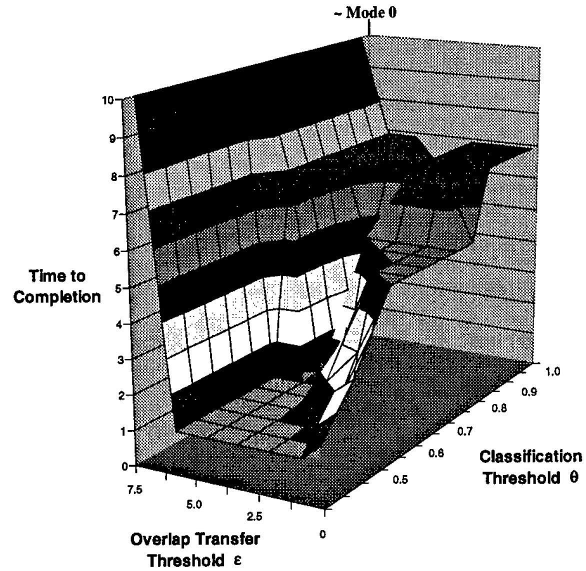


Scalability: Mission Completion Time vs Number of AVs

Mode 1 - 10 Targets



Completion Time as a Function of Information Transfer and Classification Threshold for Mode 1



10 targets
10 AVs

Summary of Rules Mediating Autonomous Network Reconfiguration

- AVs act as attractor neural networks with adaptive learning
- Overlap functions elegantly capture complex dynamic relationships
  - between individual AVs and the environment (i.e., neural network learning)
  - among AVs in the system (i.e., network of networks; scalability)
- Overlaps encode ambiguity in the system - this is a critical feature (and not a bug) - it is the source of reconfigurability
- Information at the network level based on thresholding in a noisy environment (fluctuations, incomplete data but also inherent ambiguity among overlap functions)

Implications for Communications

- **Amount of information that exceeds threshold, and requires transfer among AVs, is small**
  - **$\varepsilon > 0.8$ corresponds to 11 (1.1%) of overlaps - 10 element vector**
    1.4×10^3 (1.3×10^{-1} %) 20
    7.7×10^5 (7.2×10^{-2} %) 30
- **Contextual disambiguation is key to how AVSYS works**
- **When $\varepsilon \rightarrow 1$ and $\theta \rightarrow 1$ (i.e., Mode 0), OR when $\varepsilon \rightarrow 0$ (i.e. full communication of overlap information among AVs in Mode 1), system performance deteriorates (not solved by unlimited bandwidth)**
- **Timing of information transfer is critical for coordinating behavior of network at intermediate scales**

Summary of Achievements

04/99 – present, 3 yr award

- **Established working team at 6.1 with active 6.2 connections**
- **Leveraged ONR support with NASA / NSBRI, MGH imaging to achieve objectives on sonar and AV simulation projects**
- **Deliverables:**
  - **eNCog software, demo and documentation for scaled variance processing and mine classification (Invention disclosure; Completed AASERT supported MIT Ph.D. thesis; Applications for MCM algorithm fusion)**
  - **AVSYS software, demo and documentation for network of UUV search (Invention disclosure with UAV software, including communication specs)**
- **Uncovered rules at multiple scales (e.g., λ binning, overlap functions) within NoN that have relevance to reconfigurable networks and autonomy (FNCs)**

Future Plans

- Lake Travis site visit 3 May 2001 to better interface broadband sensor data with algorithms
- Ongoing contact with CSS as data source and evaluator of algorithms
- Enhance link between two projects via UUV and other AV systems (intelligent autonomy)
- Utilize reconfigurable NoN systems beyond current project
  - ONR / Draper tactical platform development for autonomous systems
  - NASA / NSBRI smart med systems and technology development (multi-scale incl nano-X)
  - Automated image segmentation / classification for diagnostic / therapeutic radiology and oncology
  - Industrial licensing (NewcoGen LLC)